Use of the USGS Evidence of Absence Statistical Framework to Develop Take Predictions for Indiana Bats and Northern Long-Eared Bats

1.0 INTRODUCTION

EDP Renewables has prepared a Habitat Conservation Plans (HCP) in support of an Incidental Take Permit (ITP) application for Indiana bats and northern long-eared bats (Covered Species) for the Headwaters Wind Farm (Project). HCPs include predictions of the numbers of Covered Species that will be taken and specify methods for monitoring and estimating numbers of Covered Species that have been taken to assess permit compliance. The Headwaters HCP used the Evidence of Absence (EoA; Huso et al 2015) approach to fatality estimation to develop a take prediction and monitoring for the HCP will use EoA to determine take compliance. This document describes how EoA was used to predict take (Section 5) and will be used to estimate take during monitoring (Section 4).

'Evidence of Absence' refers to a variety of different concepts. In general, it refers to a Bayesian fatality estimator (Huso et al 2015). It can also refer to a software library for the R statistical computing platform that implements some variants of the EoA estimator (EoA software; Dalthorp et al 2014)[1]. It additionally refers to the Design Tradeoffs module within the EoA software, which determines the outcome of different monitoring design parameters on the probability to detect carcasses during searches, or g. Also within the EoA software, 'Evidence of Absence' can refer to the Scenario Explorer module, which investigates likely outcomes of adaptive management regimes during the course of ITP permits via simulation. Finally, outside of the direct application of statistical methodology, 'Evidence of Absence' refers to an adaptive management framework that assumes use of the EoA estimator to track compliance with HCPs (Dalthorp and Huso 2015).

In this document, EoA refers broadly to the Bayesian fatality estimator. Reference to the software, the adaptive management framework, or other modules within the software are explicitly noted as such. The Evidence of Absence framework is rich with notation; Table 1 at the end of this appendix lists all parameters and indices used in this appendix, which models they inform, and how they are obtained.

2.0 EVIDENCE OF ABSENCE OVERVIEW

2.1 Model Form

The EoA estimator takes as inputs the number of carcasses, X, found during searches along with an estimate of the accompanying probability to detect those carcasses, g. From these, it estimates the minimum number of carcasses, m, which arrived during the study:

$$Pr(M \geq m \mid X, g) \leq \alpha \tag{1}$$

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[1] The citation is the user manual for version 1.0. The EoA software is currently in version 1.06 with version 2.0 in beta testing, but the most recent documentation is for version 1.0.

where

M is the total number of carcasses (Poisson-distributed),
m is the point estimate at the credibility level $1 - \alpha$,
X is the count of carcasses from searches (binomially-distributed),
g is the probability to detect a carcass, given that it occurred (beta-distributed), and
$1 - \alpha$ is the desired credibility for the estimate.

In the use of this model, α is specified in a way appropriate to the situation (i.e., it is driven by policy), X is known exactly from data, g is unknown and estimated as $\hat{g}$, and a prior distribution is specified for M. The estimate of fatality m is obtained by calculating the posterior distribution for M and extracting the $100(1 - \alpha)\%$ upper credible bound (or quantile) from the posterior distribution. When the desired estimate is a fatality rate rather than a total number of fatalities, EoA can estimate the posterior distribution of λ, the underlying fatality rate parameter for the Poisson distribution that generates M. That is,

$$M \sim Poisson(\lambda),\tag{2}$$

and EoA estimates the posterior of λ
$$Pr(\lambda \mid X, g).\tag{3}$$

Variants of the EoA estimator discussed in this document and available through the EoA software differ with respect to estimation of $\hat{g}$ and may differ with respect to the prior distribution assumed for $\widehat{M}$ or $\hat{\lambda}$. Otherwise, the parameters are identical to those in the EoA software.

2.1.1   Prior Distributions

EoA software versions 1.05 through 2.0 (beta), and the analyses presented in this HCP, implement a reference prior distribution for $\widehat{M}$:

$$Pr(M) \propto \int_m^{m+1} \frac{1}{\sqrt{m}}\ dm\tag{4}$$

and a Jeffrey's prior distribution for $\hat{\lambda}$:

$$Pr(\lambda) \propto \frac{1}{\sqrt{\lambda}}\tag{5}$$

Dalthorp and Huso (2015) provide the rationale for choice of these priors. The choice of prior distributions for $\widehat{M}$ and $\hat{\lambda}$ are not definitive features of the EoA estimator. The EoA software also implements uniform priors and informed priors (Dalthorp et al 2014, Huso et al 2015). At

present, the reference prior for $\tilde{M}$ and the Jeffrey's prior for $\hat{\lambda}$ are thought to be the most robust for general use, but alternatives may be developed in the future.

3.0 MODEL PARAMETERS

3.1 Estimation of *g*: Overall Probability to Observe a Carcass

A key input to the EoA fatality estimator is the probability to detect a carcass, g, given that a carcass has arrived at the wind farm. Like the choice of priors, the method to estimate g is not a definitive feature of EoA (Huso et al 2015). Analyses presented and proposed in this document calculate g following the methods in the EoA software v1.06[2]. The estimate of g is the product of the fraction of turbines searched, γ, the probability that a carcass at a searched turbine falls within a searched area, a, and the probability that a carcass falling in a searched area persists and is detected by a searcher, $\hat{\pi}$. The estimates of $\hat{\pi}$ are derived from several other models: searcher efficiency, the rate at which searcher efficiency changes with subsequent searches, k, carcass persistence, and carcass arrival phenology. Each component of g is described in turn in the following sections.

3.1.1 Probability That a Carcass Falls within a Searched Area (Weighted Distribution Method)

Fatality monitoring protocols may include search plots that are not large enough to capture all carcasses that arrive at turbines. Estimates of g include a component (area correction, a) that accounts for carcasses that may have fallen outside of searched areas (or the probability that a carcass at a searched turbine falls within a searched area), whether search plots were too small to capture all carcasses, or whether plots were irregularly shaped (e.g., road and turbine pad plots).

Carcass fall density is not uniform around turbines; rather, the relative density of carcasses nearer to turbines tends to be greater than the relative density of carcasses far from turbines (Hull and Muir 2010). It is necessary to model the fall distribution of carcasses relative to the turbine mast via distance (hereafter, "distance distribution") so that the fraction of carcasses that occur within searched areas can be estimated. Modelling the fall distribution of carcasses is complicated because the observed fall distribution is influenced by a finite search radius (i.e., the underlying distribution is truncated) and because the observed fall distribution is distorted by unequal detection probability based on carcass distance from turbines. For these reasons, calculating the area correction, a, is complicated.

Area correction, a, is calculated by estimating the proportion of carcasses expected to fall within searched areas:

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[2] These methods are not formally documented elsewhere but are described here based on a close reading of the EoA software code.

$$a = \sum_{x=1}^{u} H_x \times \sigma_x \qquad (6)$$

where a is the area correction factor, x indexes a series of 1-m-wide annuli centered on the turbine, u is the maximum search radius in meters, σ_x is the fraction of the xth annulus searched (calculated in a Geographic Information System), and H_x is the proportion of all carcasses occurring within the xth annulus.

H_x is calculated as

$$Pr(x-1 < Y < x) = H_x = \int_{x-1}^{x} h(y|\hat{\theta}) \, dy \qquad (7)$$

where $h(x)$ is the estimated distance distribution of carcasses (from turbine center) and $\hat{\theta}$ are the parameters associated with the distance distribution.

The distance distribution of carcasses (from turbines) is assumed to follow one of six probability distributions (normal, gamma, Weibull, log-logistic, Gompertz, or Rayleigh), and sample-size corrected Akaike's Information Criterion (AICc) is used to select the best model for the available data. The raw observed distances of carcasses from turbines (hereafter, "observed distance distribution") do not represent the true underlying distance distribution because the proportion of searchable area may vary with distance from turbine. Also, the carcass distance data may be aggregated over several search strata with different detection probabilities.

A maximum likelihood estimation approach (MLE) is used to fit a weighted distribution (D. Dalthorp, USGS, pers. comm.) to the data, where the weights reflect relative probabilities of detection to account for the divergence between the observed and underlying distance distributions.

If the underlying distance distribution is described by some probability density function, $h(x|\theta)$, where x is distance from the turbine, θ is the associated parameter vector, and the weights are described by a function, $w(x)$, then the weighted distribution is:

$$h^*(x|\theta) = \frac{w(x) \times h(x|\theta)}{\int_0^{\infty} w(y) \times h(y|\theta) dy} \qquad (8)$$

where the $w(x)$ in the numerator accounts for the distortion of the underlying distance distribution, $h(x|\theta)$, that arises due to variable detection probability, and the integral in the denominator ensures that the weighted distribution is still a valid probability function.

Although the parameters, $\hat{\theta}$ are obtained by maximizing the likelihood associated with $h^*(x|\theta)$, the underlying density distribution in Equation (7) is approximated as $h(x|\hat{\theta})$.

By using $h(x|\hat{\theta})$ in (7) the area correction accounts for differential detection probabilities within search areas, as well as carcasses that may have fallen beyond the boundaries of the search area.

The weight function needs to include any factor that influences the probability to detect a carcass. Although some components of the weight function are not individually distance-dependent, they become so when combined with data across several search strata with different search radii. The weight function is difficult to approximate because most of its components need to be estimated. The weight function is approximated as

$$w(x) = \frac{\sum_{z=1}^{n} \pi_z \times \lambda_z \times \sigma_{z,x} \times t_z}{\sum_{z=1}^{n} t_z},$$
(9)

for distances from $0 \leq x \leq r$ meters, and assigned a value of 0 for all other distances. In Equation (9), *n* is the number of search strata represented in the sample, π_z is the detection probability for a carcass in stratum *z* (see section below: *Probability that a carcass falling in a searched area persists and is detected by a searcher*), λ_z is the fatality rate in stratum *z*, t_z is the number of turbines included in stratum *z*, and $\sigma_{z,x}$ is the average proportion of area searched in the xth annulus in stratum *z*. If all of the search strata contributing data to the weighted distribution estimate have the same search radius, the weight function can be simplified to:

$$w(x) = \pi_z \times \sigma_{z,x}$$
(10)

because fatality rates do not vary systematically with search plot size.

3.1.2 Searcher Efficiency

Searcher efficiency is the probability that a searcher will successfully detect a carcass that is present within the search area during a search.

Searcher efficiency p follows a simple binomial model and is estimated from experimental trials as:

$$\hat{p} = \frac{number\ of\ trial\ carcasses\ that\ were\ detected\ by\ searchers}{number\ of\ trial\ carcasses\ that\ were\ available\ to\ searchers}$$
(11)

3.1.3 Change in Searcher Efficiency through Successive Searches

For a given carcass, searcher efficiency is not constant through time, but changes with successive searches. First, carcasses decay and eventually disintegrate as they age. Second, easy-to-see carcasses are more readily detected during earlier searches, meaning that carcasses that remain through subsequent searches tend to be inherently more difficult to see.

If searcher efficiency is assumed constant through time, estimates of detection probability will be biased high, and fatality estimates will be biased low, and the converse also holds. Accurate

fatality estimates that make best use of the search data require an understanding of how searcher efficiency changes through time.

The multiplicative parameter k describes changing searcher efficiency through time via:

$$p_{j+1} = p_j \times k \qquad (12)$$

where p_j is the searcher efficiency on the jth search.

Estimating k requires that searcher efficiency trial carcasses be deployed and left in place through multiple searches, and generally requires large numbers of trial carcasses to ensure adequate sample size beyond the first search. When data that track trial carcasses through a number of searches are available, searcher efficiency can be calculated for successive searches (p_j, where j is an index for searches) and k can be estimated using Bayesian or frequentist methods.

Data to estimate k often are not available. Huso et al. (*in press*) have analyzed bat searcher efficiency data from numerous studies in North America and suggest that in the absence of data, 0.67 is a reasonable value to use for k for bats. A value of 0.67 means that if searcher efficiency is p for a carcass that has been subjected to no previous searches, it will be $p \times 0.67$ for a carcass that has been available for one search (and missed), $p \times 0.67^2$ for a carcass that has been available for two searches (and missed), and so-on.

3.1.4 Carcass Persistence

Not all carcasses that arrive at the wind farm persist on the landscape long enough to be discovered. Scavengers, agricultural activity, or other forces may remove carcasses before searchers have an opportunity to detect them. The average probability of persistence of a carcass is estimated from an interval-censored survival model (Huso et al 2012). Given a search interval of length I, the Huso et al. (2012) approach estimates the average probability that a carcass arriving $\{0, 1, 2, \ldots, I\}$ days before the search will persist until the search. Assuming carcass persistence times follow a probability distribution $f(d)$ with cumulative probability function $F(d)$, the probability of "survival," or persistence, until day d is $1 - F(d)$. If carcass arrival is uniform in time so that the probability of arrival is constant between 0 and I, the average persistence probability r until the first search after a carcass arrives is:

$$r_{1,1} = \frac{\int_0^I 1 - F(d)\, dd}{I} \qquad (13)$$

A minor modification of this formula accommodates carcasses that may be missed on the first search and discovered on a subsequent search (the jth search). The average probability that a carcass which has persisted from the $(j-1)^{th}$ search also persists until the jth search is:

$$r_{1,j} = \frac{\int_{(j-1) \times I}^{J \times I} 1 - F(d)\, dd}{\int_{(j-2) \times I}^{(j-1) \times I} 1 - F(d)\, dd} \qquad (14)$$

where $j \geq 2$.

3.1.5 Carcass Arrival Phenology

The detection probability for any particular carcass depends on when it arrives at the wind farm. This is because carcasses that arrive earlier during the study period have the potential to persist through more searches, and therefore have more opportunities to be discovered than carcasses arriving later in the study period. Assume that there are q searches during the study period that occur on days $\{d_1, d_2, \dots d_q\}$ and assume there are no carcasses available when the study period begins on day $d_0 = 0$. The time interval $\{d_{i-1}, \dots, d_i$ is the ith arrival interval, and the proportion of carcasses arriving during the ith arrival interval is c_i, where we ensure that all of the carcasses arrive during an interval by ensuring that,

$$\sum_{i=1}^{q} c_i = 1.0 \qquad (15)$$

Equality of all of the c_i implies the same relative arrival rate of carcasses between each search interval (i.e., over the entire study period). This would be the case if, for example, the arrival phenology of carcasses is uniform in time and the search interval is constant between searches. The c_i can be adjusted to reflect non-constant arrival phenology, non-constant search interval, or both.

When carcass arrival is pulsed (as it may be if there is a seasonal migration), it is likely that the relative abundance of carcasses during a pulse forms a bell-shaped curve, but it is rare to have appropriate data to estimate the shape of the curve. Even with adequate carcass arrival data, large year-to-year variation in phenology precludes the assumption that one year's estimate will be adequate to predict for a subsequent year.

Consequently, arrival phenology is assumed to be uniform through the intervals within a season and adjustments to the c_i are made on the basis of relative fatality rates from season to season. If seasonal and annual fatality estimates are not available for the target species, fatality estimates for a larger group of species (e.g., all bats) may be used as a surrogate.

3.1.6 Probability That a Carcass Falls in a Searched Area Persists and is Detected by a Searcher

The probability that a carcass arrived during the ith interval persists and is detected on the ith or subsequent searches (*interval-specific detection probability*) is calculated recursively for each search from i to q, where q is the last search. The probability that a carcass persists and is detected on the first search after arrival is:

$$\pi_{i,i} = r_{i,i} \times p \tag{16}$$

where $r_{i,i}$ is the probability of persistence (Equation 14) and p is the probability of detection (Equation 11). The probability that the carcass persists and is detected on the second or subsequent searches after arrival is:

$$\pi_{i,j} = \pi_{i,i} + \Sigma_{\psi=i+1}^{j}\left(1 - \pi_{i,\psi-1}\right) \times \left(r_{i,\psi} \times p \times k^{\psi-i}\right) \tag{17}$$

where $\pi_{i,j}$ is the probability that a carcass arriving during the ith interval persists and is detected during the jth search and k is the factor by which searcher efficiency changes from one search to the next.

For a study with a total of q search intervals, $\pi_{i,j}$ can be calculated for any $0 \le i \le j \le q$, but in practice we are interested in the probability that a carcass arriving during the ith interval is detected at *some* point before the end of the study, i.e. $\pi_{i,q}$.

The first element of the product in the summand of Equation (17) represents the probability that the carcass is missed during all previous searches and the second element of the product in the summand of Equation (17) represents the probability that the carcass is discovered during the jth search.

The overall probability of detection for a carcass is the average of the interval-specific arrival probabilities weighted by the arrival fraction c_i:

$$\pi = \Sigma_{i=1}^{q}\pi_{i,q} \times c_i. \tag{18}$$

3.1.7   Overall Probability of Carcass Detection

For a wind farm with z search strata having T_z turbines in each of the z strata, of which t_z are searched, the overall probability that a carcass arriving at the wind farm will fall in a searched area, remain available for searchers, and be detected is:

$$g = \Sigma_{i=1}^{z}\frac{t_i}{T_i} \times a_i \times \pi_i \tag{19}$$

The variance of this estimator is unknown. Bootstrap resampling procedures are used to approximate confidence intervals for this estimator when required.

4.0   FATALITY ESTIMATION

Fatality estimation in EoA is straightforward: carcass counts and probabilities of detection are analyzed using EoA, and a take estimate M is obtained with the desired level of credibility.

4.1   Single-Site, Single-Year Fatality Estimation

The EoA software provides functionality to calculate a fatality estimate for a single site during a single year. The estimating model is exactly as given in Section 2.1.1 – *Model Form*. This module of the EoA software is the only module that calculates g based on user-supplied information about the arrival function, search schedule, probability that a carcass falls in a searched area, searcher efficiency, and carcass persistence. The form of the information accepted by the software varies by version; Versions 2.0 (beta) and higher return g as the two parameters that describe a beta distribution, while earlier versions return g with 95% confidence intervals, calculated in Section 3.1.7 – *Overall Probability of Carcass Detection*.

The EoA software takes the probability of carcass detection, g, and the count of carcasses from searches, X, as inputs and returns the posterior distribution of total fatality. Versions 2.0 and later also return the posterior distribution of the fatality rate, λ.

4.2   Multiple Year (or Multiple Season) Fatality Estimation

When data are available from multiple search periods (years or seasons), the EoA software can provide a cumulative estimate of fatality that covers the entire search history. The estimating model is exactly as given in Section 2.1.1 – *Model Form*. Inputs to the EoA software are in the form of a matrix with one row for each search period.

For versions 1.06 and earlier, the columns contain carcass counts, the point estimate of g, upper and lower 95% confidence bounds for g, and annual weights. For versions 2.0 and later, the columns contain carcass counts, the two parameters of a beta distribution that describe g, and annual weights. The annual weights are proportional to the expected relative fatality rates for each sampling period.

Although fatality rates are unknown, weights may vary with wind farm size (if, for example, a wind farm doubles in size between two sample periods) or with adaptive management actions (e.g., a wind farm implements an adaptive management action that is expected to reduce fatality by half). The weights are used to calculate a weighted average g:

$$g = \frac{\sum_{b=1}^{sampling\ periods} g_b \times v_b}{\sum_{b=1}^{sampling\ periods} v_b} \qquad (20)$$

where g_b and v_b are the sampling-period-specific probabilities of detection and weights, respectively.

The multiple year module of the EoA software returns an estimate of total cumulative fatality, M, or an estimate of the average fatality rate, λ. If λ is returned, it carries units of carcasses per

wind farm per sampling period and it is scaled to be relative to a wind farm operating with a weight of 1.0.

4.3   Multiple Site (or Search Stratum) Fatality Estimation

When data are available from multiple sites or multiple search strata within a site, the EoA software can provide a cumulative estimate of fatality covering the entire searched area. The estimating model is exactly as given in Section 2.1.1 – *Model Form*. Inputs to the EoA software are in the form of a matrix with one row for each stratum.

For versions 1.06 and earlier, the columns contain carcass counts, the point estimate of π, upper and lower 95% confidence bounds for π, and stratum weights. For versions 2.0 and later, the columns contain carcass counts, the two parameters of a beta distribution that describe π, and stratum weights.

The stratum weights are the fraction of carcasses that are expected to fall within each search stratum (i.e., a from Section 3.1.6 – *Probability That a Carcass Falls in a Searched Area Persists and is Detected by a Searcher*). In version 2.0 and later, the stratum weights must sum to 1.0 and the input matrix always includes an unsearched stratum (with $\pi = 0$) to account for unsearched turbines or areas.

The weights are used to calculate a weighted average g:

$$g = \sum_{z=1}^{sampling\ strata} \pi_z \times a_z \qquad (21)$$

where π_z and a_z are the stratum-specific probabilities of detection and area corrections, respectively.

The multiple site module of the EoA software will return an estimate of total fatality, M, or an estimate of the fatality rate, λ. If λ is returned it carries units of carcasses per sampling period and it covers the entire area represented within the input data table.

4.4   Selecting Credible Bounds from Evidence of Absence Estimates

Because EoA is a Bayesian model, the estimates it returns are distributions of total take, or the take rate. When a single number is needed to set a threshold or determine compliance, it is necessary to select a credible bound from the posterior distribution. There is no objective way to select credible bounds; the decision is based on a subjective assessment of the risks of setting the wrong threshold that would result in being in noncompliance with an incidental take permit (ITP). In general, the 50th credible bound, or median of the distribution, is a good value to use for a point estimate: in this case, there is 50% confidence that the true value is not greater than that estimated value. As larger credible bounds are chosen, confidence increases that the true value will not be larger than the estimated value.

5.0   FATALITY PREDICTION

It is often desirable to obtain fatality predictions based on past fatality estimates but unless a fatality prediction is desired for the same time interval and the same area that informed the prediction, it is not possible to use the estimate of M in fatality prediction. The estimate of M is specific to the duration, area, and operational regime (i.e., turbine cut-in speed) where data were collected. Similarly, an estimate of M that is calculated for a wind farm with two equally-sized phases cannot be rescaled to represent one phase of the wind farm. This is because M is a credible bound from a Poisson posterior, and the quantiles of Poisson distributions do not scale in a linear way.

When a fatality prediction is needed, the procedure is to estimate the fatality rate, λ, for a wind farm that is sufficiently comparable to the wind farm for which a prediction is desired. Unlike M, the credible bounds of λ can be rescaled to represent larger or smaller facilities, or longer or shorter time periods, or facilities with different operational regimes. For example, if λ is estimated (at a desired level of credibility: Q_λ) for a wind farm with 100 turbines over a 2-year period and a prediction is needed for a 200-turbine wind farm for 30 years, the predicted fatality rate (with the same Q_λ) will be $\lambda_{pred} = 2 \times 15 \times \lambda$.

Getting from λ_{pred} to a predicted number of fatalities for the purpose of developing a take prediction to set a take authorization number for an ITP requires the selection of a credible bound (Q_M) for the prediction of M. The predicted number of fatalities is then the Q_M credible bound (= Q_M quantile) from a Poisson distribution with a rate parameter equal to λ_{pred}.

6.0   MONITORING DESIGN

The EoA software has a *Design tradeoffs* module that is useful when designing fatality monitoring. The module calculates g as described in Section 3.1 – *Estimation of g: Overall Probability to Observe a Carcass* given user input and returns the results in graphical format.

Table 1. Parameters and indices used in this appendix, which models they inform, and how they are obtained.

Parameter	Definition	How Obtained	Models in Which it is Used
α	One minus the credibility of an estimate	Subjective decision	
a	area correction- the proportion of carcasses expected to fall within searched areas	Estimated	Overall probability of detection
b	Index for sampling periods within a multiple-year or multiple-season EoA estimate	Index	Evidence of Absence

c_i	Fraction of carcasses arriving during the ith interval	Assumed uniform within seasons; Estimated among seasons	Overall probability of detection
d	Time (days) to carcass removal	Function input	Carcass persistence
$f(d)$	Probability distribution function for persistence times (d; days) of carcasses	Estimated	Carcass persistence
$F(d)$	Cumulative distribution function for persistence times (d; days) of carcasses	Estimated	Carcass persistence
g	Overall probability that a carcass arriving at the wind farm persists and is detected by searchers	Estimated	Overall probability of detection
$g_{i,j}$	Probability that a carcass arriving during the ith interval persists until and is discovered during the jth interval, conditional on having persisted until the $j-1^{th}$ interval	Estimated	Overall probability of detection
γ	Proportion of turbines searched	Known	Overall probability of detection
H_x	Proportion of carcasses in the annulus that covers between $x-1$ and x meters from turbines	Estimated	Area correction
$h(x \mid \theta)$	Probability distribution function for distances (x; meters) of carcasses from turbines	Estimated	Distance distribution
$h^*(x \mid \theta)$	Weighted probability distribution function for distances (x; meters) of carcasses from turbines	Estimated	Distance distribution
I	Duration of search interval; number of days between searches	Known	Carcass persistence
i	Index for intervals	Index	Carcass persistence, overall probability of detection
j	Index for searches	Index	Carcass persistence, overall probability of detection
k	Factor by which searcher efficiency (p) changes between searches	Assumed ($k = 0.67$) or estimated	Overall probability of detection
λ	Fatality rate	Estimated	Model form
M	Total fatality	Estimated	Model form

n	Number of search strata contributing data to the distance distribution ($h^*(x \mid \theta)$) of carcasses from turbines	Known	Distance distribution of carcasses
p	Searcher efficiency; this is the probability that a carcass that is in a search area during a search is detected by a searcher	Estimated	Overall probability of detection
Pr	Abbreviation for *Probability*	Abbreviation	
π	Probability that a carcass within a searched area will be available to searchers and detected	Estimated	Overall probability of detection
Q	Credible bound for estimation or prediction of λ or M	Subjectively selected	Fatality estimation
q	Number of searches and search intervals during the study	Known from field data	Overall probability of detection
$r_{i,j}$	Average probability that a carcass arriving during interval i persists until search j	Estimated	Carcass persistence, overall probability of detection
s	Index for carcasses informing the distance distribution	Index	Distance distribution
S	Total number of carcasses informing the distance distribution	Known from field data	Distance distribution
σ_x	Average proportion of area searched between $x-1$ meters and x meters from the turbine	Estimated in GIS	Distance distribution
$\sigma_{z,x}$	Average proportion of area searched between $x-1$ meters and x meters from the turbine in stratum z	Estimated in GIS	Distance distribution
T_z	Total number of turbines in sampling stratum z	Known from field data	Distance distribution
t_z	Number of turbines sampled within a sampling stratum z	Known from field data	Distance distribution
θ	Parameters associated with the probability distribution function for distances of carcasses from turbines $h(x \mid \theta)$	Estimated	Distance distribution
$\hat{\theta}$	Estimated parameters associated with the weighted probability distribution function for distances of carcasses from turbines $h^*(x \mid \theta)$	Estimated	Distance distribution
u	Maximum search distance (meters)	Known from field data	Distance distribution

v	Sampling period weights for a multiple-year or multiple-season EoA estimate	Estimated	Searcher efficiency, overall probability of detection
$w(x)$	Weighting function (of distance, x; meters) used to fit the weighted distance distribution of carcasses from turbines ($h^{\cdot}(x \mid \theta)$)	Estimated	Distance distribution
X	Count of carcasses from monitoring searches	Known from data	Model form
x	Distance (meters) of carcasses from turbines	Function input	Distance distribution
z	Index for search strata	Index	Distance distribution, overall probability of detection

7.0 LITERATURE CITED

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